Project 7: Difference-in-Differences and Synthetic Control

```
# Install and load packages
if (!require("pacman")) install.packages("pacman")
```

```
## Loading required package: pacman
```

```
devtools::install_github("ebenmichael/augsynth")
```

```
## Skipping install of 'augsynth' from a github remote, the SHA1 (0f4f1bcc) has not changed since last i
##   Use 'force = TRUE' to force installation
```

```
pacman::p_load(# Tidyverse packages including dplyr and ggplot2
               tidyverse,
               ggthemes,
               augsynth,
               gsynth)

# set seed
set.seed(44)

# load data
medicaid_expansion <- read_csv('/Users/stacyworkuser/Downloads/medicaid_expansion.csv')
```

```
## Rows: 663 Columns: 5
```

```
## -- Column specification --------------------------------------------------------
## Delimiter: ","
## chr  (1): State
## dbl  (3): year, uninsured_rate, population
## date (1): Date_Adopted
##
## i Use 'spec()' to retrieve the full column specification for this data.
## i Specify the column types or set 'show_col_types = FALSE' to quiet this message.
```

```
options(scipen=999)
```

Introduction

For this project, you will explore the question of whether the Affordable Care Act increased health insurance coverage (or conversely, decreased the number of people who are uninsured). The ACA was passed in March 2010, but several of its provisions were phased in over a few years. The ACA instituted the "individual mandate" which required that all Americans must carry health insurance, or else suffer a tax penalty. There are four mechanisms for how the ACA aims to reduce the uninsured population:

- Require companies with more than 50 employees to provide health insurance.
- Build state-run healthcare markets ("exchanges") for individuals to purchase health insurance.
- Provide subsidies to middle income individuals and families who do not qualify for employer based coverage.
- Expand Medicaid to require that states grant eligibility to all citizens and legal residents earning up to 138% of the federal poverty line. The federal government would initially pay 100% of the costs of this expansion, and over a period of 5 years the burden would shift so the federal government would pay 90% and the states would pay 10%.

In 2012, the Supreme Court heard the landmark case NFIB v. Sebelius, which principally challenged the constitutionality of the law under the theory that Congress could not institute an individual mandate. The Supreme Court ultimately upheld the individual mandate under Congress's taxation power, but struck down the requirement that states must expand Medicaid as impermissible subordination of the states to the federal government. Subsequently, several states refused to expand Medicaid when the program began on January 1, 2014. This refusal created the "Medicaid coverage gap" where there are indivudals who earn too much to qualify for Medicaid under the old standards, but too little to qualify for the ACA subsidies targeted at middle-income individuals.

States that refused to expand Medicaid principally cited the cost as the primary factor. Critics pointed out however, that the decision not to expand primarily broke down along partisan lines. In the years since the initial expansion, several states have opted into the program, either because of a change in the governing party, or because voters directly approved expansion via a ballot initiative.

You will explore the question of whether Medicaid expansion reduced the uninsured population in the U.S. in the 7 years since it went into effect. To address this question, you will use difference-in-differences estimation, and synthetic control.

Data

The dataset you will work with has been assembled from a few different sources about Medicaid. The key variables are:

- **State**: Full name of state
- **Medicaid Expansion Adoption**: Date that the state adopted the Medicaid expansion, if it did so.
- **Year**: Year of observation.
- **Uninsured rate**: State uninsured rate in that year.

Exploratory Data Analysis

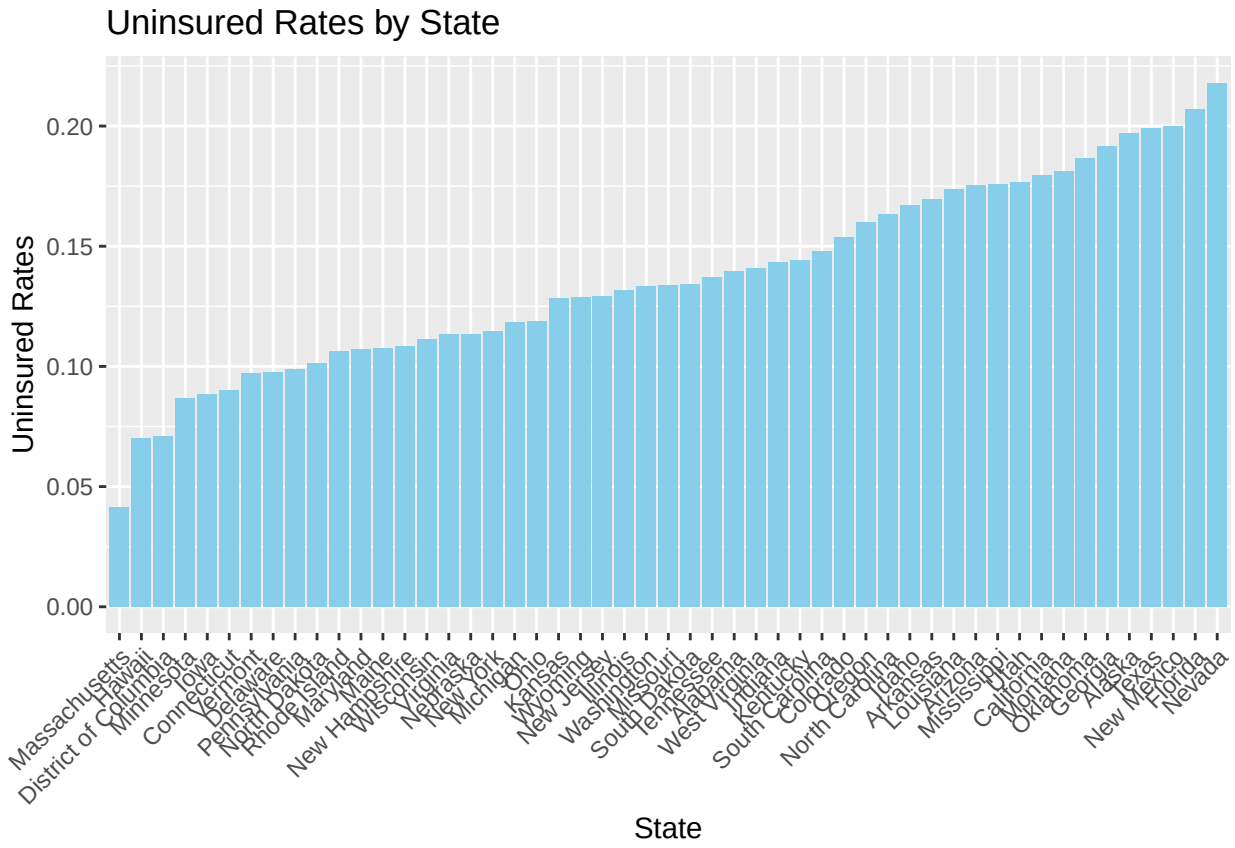
Create plots and provide 1-2 sentence analyses to answer the following questions:

- Which states had the highest uninsured rates prior to 2014? The lowest? Nevada had the highest average uninsured rate in the years prior to 2014 (2008- 2013), Massachusetts has the lowest uninsured rates.
- Which states were home to most uninsured Americans prior to 2014? How about in the last year in the data set? **Note**: 2010 state population is provided as a variable to answer this question. In an actual study you would likely use population estimates over time, but to simplify you can assume these numbers stay about the same. California and then Texas has the most uninsured Americans prior to 2014. After implementation Texas has the highest uninsured population, California is second place.

```r
df_avg <- medicaid_expansion %>%
  filter(year >= 2008 & year <= 2013) %>%
  group_by(State) %>%
  summarise(avg_uninsured_rate = mean(uninsured_rate, na.rm = TRUE))

# highest and lowest uninsured rates
df_sorted <- df_avg[order(df_avg$avg_uninsured_rate), ]

# Create a bar plot using ggplot
ggplot(df_sorted, aes(x = reorder(State, avg_uninsured_rate), y = avg_uninsured_rate)) +
  geom_bar(stat = "identity", fill = "skyblue") +
  labs(title = "Uninsured Rates by State",
       x = "State",
       y = "Uninsured Rates") +
  theme(axis.text.x = element_text(angle = 45, hjust = 1))
```

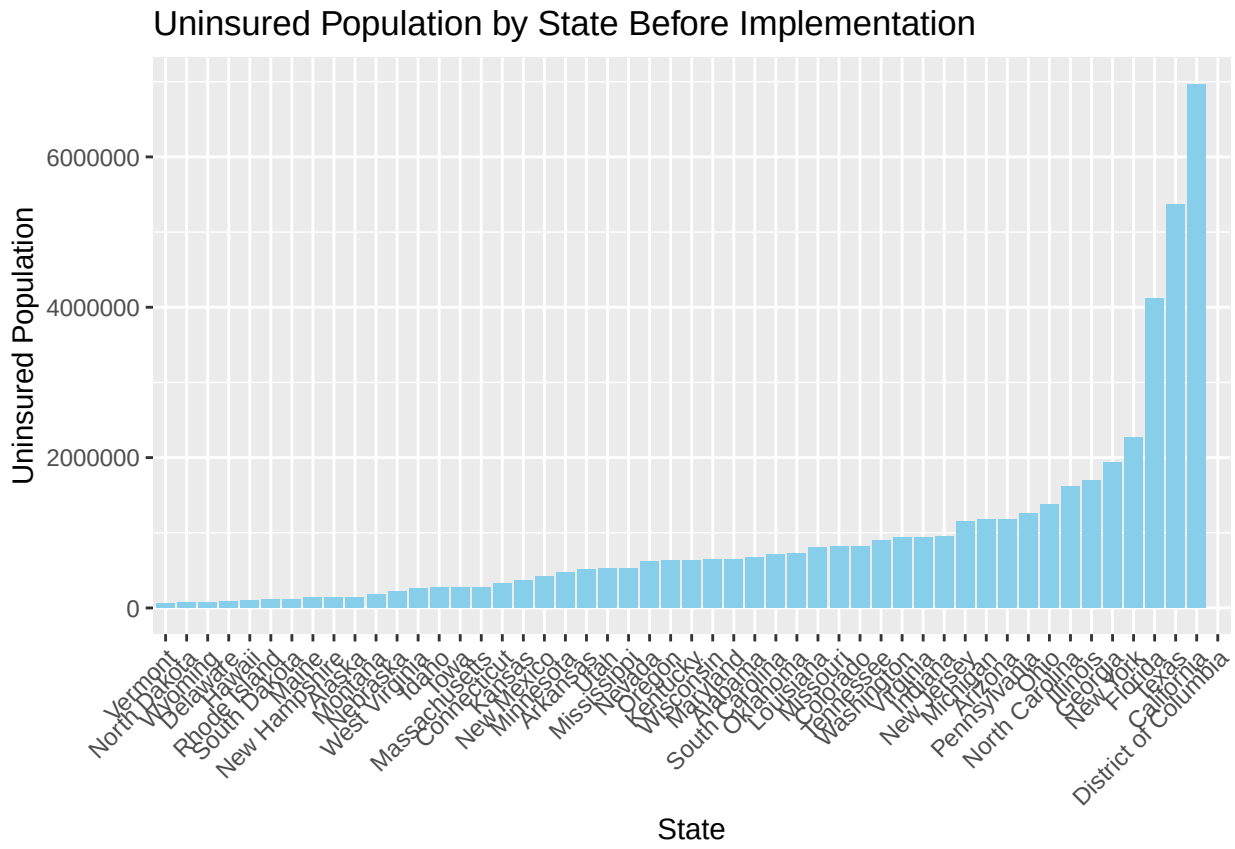



```r
df_avg <- medicaid_expansion %>%
  filter(year >= 2008 & year <= 2013) %>%
  mutate(uninsured_pop = uninsured_rate * population) %>%
  group_by(State) %>%
  summarise(avg_uninsured_pop = mean(uninsured_pop, na.rm = TRUE))

# highest and lowest uninsured rates
df_sorted <- df_avg[order(df_avg$avg_uninsured_pop), ]
```

```
# Create a bar plot using ggplot
ggplot(df_sorted, aes(x = reorder(State, avg_uninsured_pop), y = avg_uninsured_pop)) +
  geom_bar(stat = "identity", fill = "skyblue") +
  labs(title = "Uninsured Population by State Before Implementation",
       x = "State",
       y = "Uninsured Population") +
  theme(axis.text.x = element_text(angle = 45, hjust = 1))
```

```
## Warning: Removed 1 row containing missing values or values outside the scale range
## (`geom_bar()`).
```



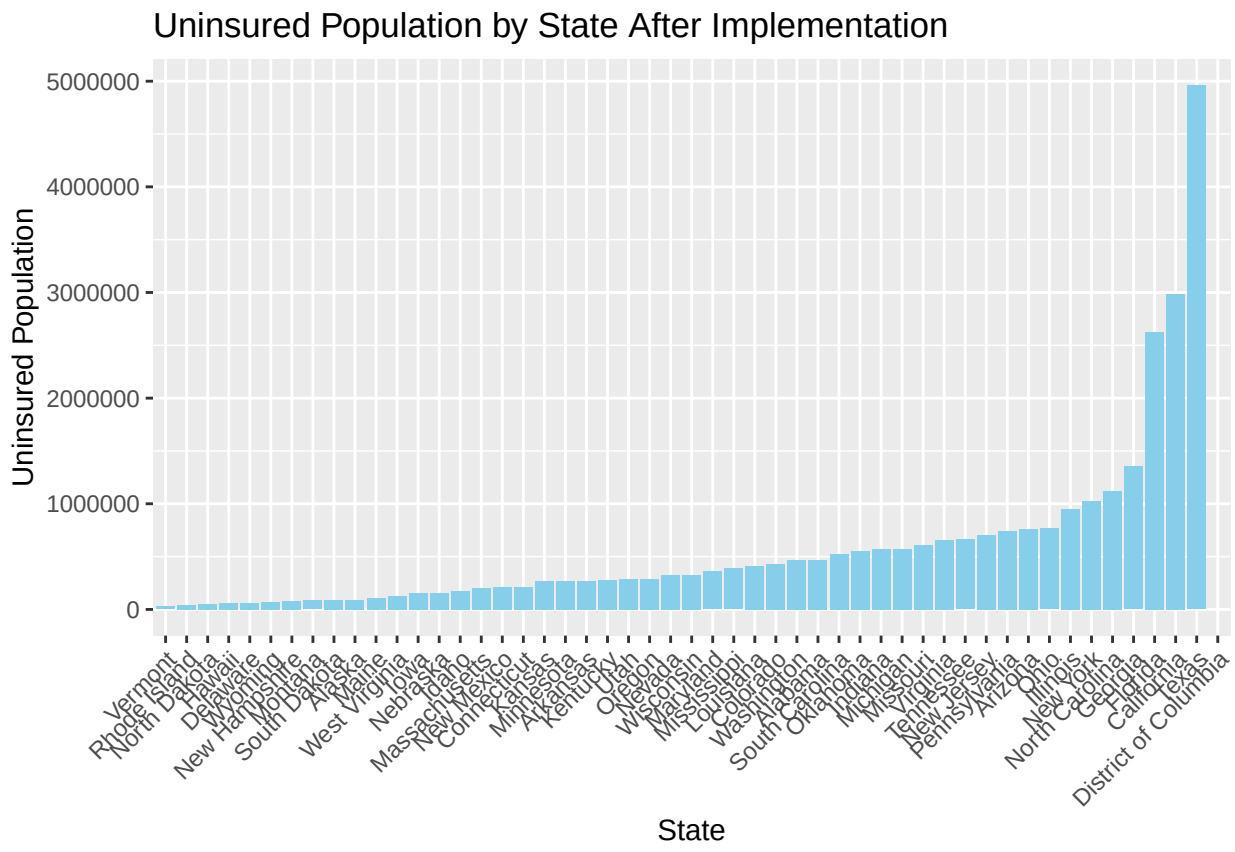

```
df_avg <- medicaid_expansion %>%
  filter(year == 2020) %>%
  mutate(uninsured_pop = uninsured_rate * population) %>%
  group_by(State) %>%
  summarise(avg_uninsured_pop = mean(uninsured_pop, na.rm = TRUE))

# highest and lowest uninsured rates
df_sorted <- df_avg[order(df_avg$avg_uninsured_pop), ]

# Create a bar plot using ggplot
ggplot(df_sorted, aes(x = reorder(State, avg_uninsured_pop), y = avg_uninsured_pop)) +
  geom_bar(stat = "identity", fill = "skyblue") +
  labs(title = "Uninsured Population by State After Implementation",
```

```
       x = "State",
       y = "Uninsured Population") +
  theme(axis.text.x = element_text(angle = 45, hjust = 1))
```

```
## Warning: Removed 1 row containing missing values or values outside the scale range
## (`geom_bar()`).
```



Difference-in-Differences Estimation

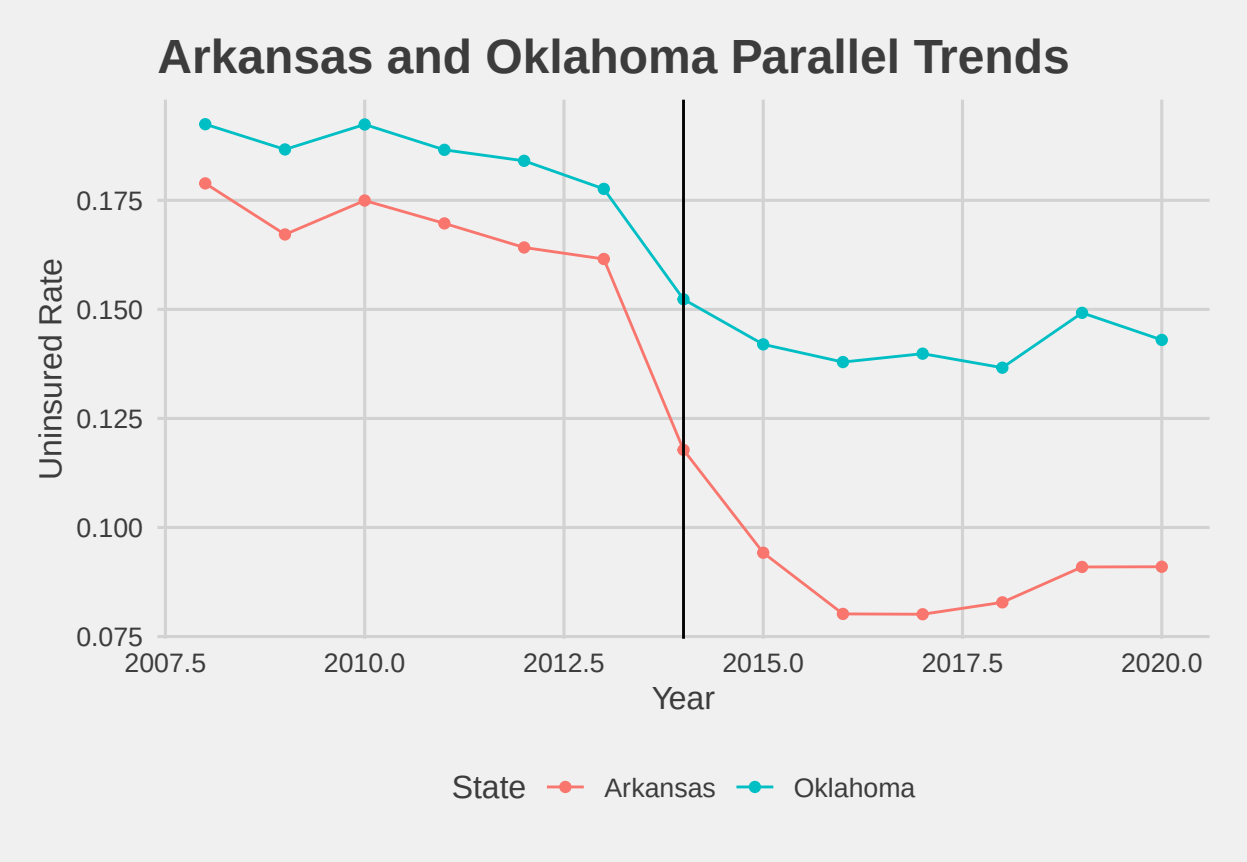
Estimate Model

Do the following:

- Choose a state that adopted the Medicaid expansion on January 1, 2014 and a state that did not. **Hint**: Do not pick Massachusetts as it passed a universal healthcare law in 2006, and also avoid picking a state that adopted the Medicaid expansion between 2014 and 2015.
- Assess the parallel trends assumption for your choices using a plot. If you are not satisfied that the assumption has been met, pick another state and try again (but detail the states you tried).

```
# Parallel Trends plot
# -----------------------------------------------------------------
medicaid_expansion %>%
```

```r
# process
# ---------
filter(State %in% c("Arkansas","Oklahoma")) %>%
# plotting all of the time periods -- not filtering out any of them
# plot
# ---------
ggplot() +
# add in point layer
geom_point(aes(x = year,
               y = uninsured_rate,
               color = State)) +
# add in line layer
geom_line(aes(x = year,
              y = uninsured_rate,
              color = State)) +
# add a horizontal line
geom_vline(aes(xintercept = 2014)) +
# themes
theme_fivethirtyeight() +
theme(axis.title = element_text()) +
# labels
ggtitle('Arkansas and Oklahoma Parallel Trends') +
xlab('Year') +
ylab('Uninsured Rate')
```



- Estimates a difference-in-differences estimate of the effect of the Medicaid expansion on the uninsured share of the population. You may follow the lab example where we estimate the differences in one pre-treatment and one post-treatment period, or take an average of the pre-treatment and post-treatment outcomes

```
medicaid_expansion_states <-
  medicaid_expansion %>%
  mutate(treatment = case_when(State == "Arkansas" & year >= 2014 ~ 1, TRUE ~ 0)) %>%
  filter(State %in% c("Arkansas", "Oklahoma"))

medicaid_expansion <-
  medicaid_expansion %>%
  mutate(treatment = case_when(State == "Arkansas" & year >= 2014 ~ 1, TRUE ~ 0))

# multisynth model states
multi <- medicaid_expansion %>%
    filter(!State %in% c("District of Columbia")) %>%
    mutate(treated = ifelse(year >= year(Date_Adopted), 1, 0))

                # pre-treatment difference
pre_diff <- medicaid_expansion %>%
  # filter out only the quarter we want
  filter(year == 2013) %>%
  # subset to select only vars we want
  select(State,
         uninsured_rate) %>%
  # make the data wide
  pivot_wider(names_from = State,
              values_from = uninsured_rate) %>%
  # subtract to make calculation
  summarise(Oklahoma - Arkansas)

# post-treatment difference
# ----------
post_diff <-
  medicaid_expansion %>%
  # filter out only the quarter we want
  filter(year == 2015) %>%
  # subset to select only vars we want
  select(State,
         uninsured_rate) %>%
  # make the data wide
  pivot_wider(names_from = State,
              values_from = uninsured_rate) %>%
  # subtract to make calculation
  summarise(Oklahoma - Arkansas)

# diff-in-diffs
# ----------
diff_in_diffs <- post_diff - pre_diff
diff_in_diffs
```

```
##   Oklahoma - Arkansas
## 1              0.0317
```

Discussion Questions

- Card/Krueger's original piece utilized the fact that towns on either side of the Delaware river are likely to be quite similar to one another in terms of demographics, economics, etc. Why is that intuition harder to replicate with this data?
- **Answer**: It's hard with this data because there are a lot of differences between states that make states a harder comparison than comparing towns. For one, Medicaid expansion only occurs when one political party is in charge (or ballot measure) and Medicaid expansion is very polarizing– this is already one difference from Card/Krueger. Second, in my view, the insurance expansion "treatment" is less likely to have "compliance" since states can do a better or worse job at enrolling, or create barriers such as work requirements (barrier due to reporting requirements).
- What are the strengths and weaknesses of using the parallel trends assumption in difference-in-differences estimates?
- **Answer**: Parallel trends assumption works intuitively for readers since it doesn't necessarily require every covariate to match– it creates a natural control group w/ causal interpretation using observational data. Some weaknesses of parallel trends is that it may be hard to test whether parallel trends hold or if it is due to chance. It can also be sensitive to the DiD model, so we would need additional sensitivity analyses to ensure that the treatment effect holds. In my case, in this exercise above, I find that it can be somewhat arbitrary: I could choose a control state that has parallel trends and has a larger or smaller effect size post treatment.

Synthetic Control

Estimate Synthetic Control

Although several states did not expand Medicaid on January 1, 2014, many did later on. In some cases, a Democratic governor was elected and pushed for a state budget that included the Medicaid expansion, whereas in others voters approved expansion via a ballot initiative. The 2018 election was a watershed moment where several Republican-leaning states elected Democratic governors and approved Medicaid expansion. In cases with a ballot initiative, the state legislature and governor still must implement the results via legislation. For instance, Idaho voters approved a Medicaid expansion in the 2018 election, but it was not implemented in the state budget until late 2019, with enrollment beginning in 2020.

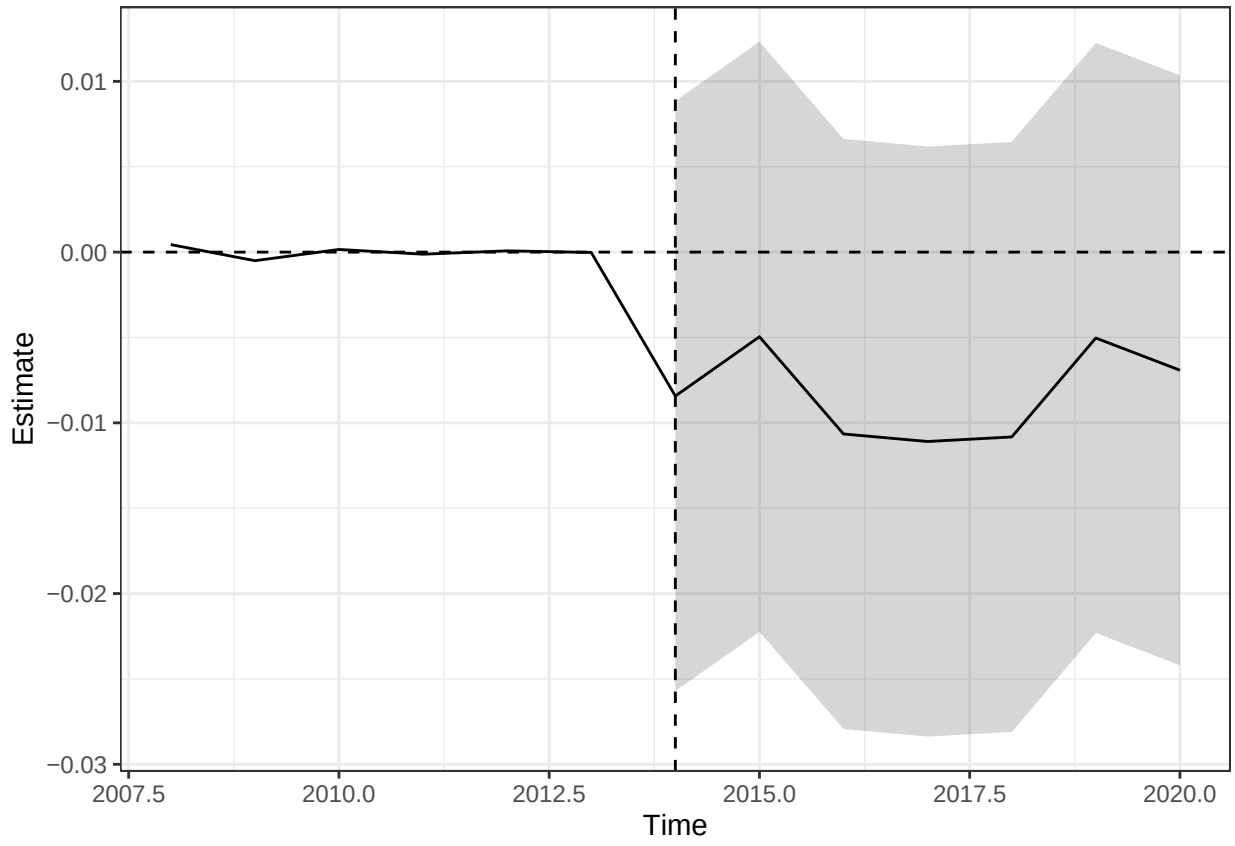
Do the following:

- Choose a state that adopted the Medicaid expansion after January 1, 2014. Construct a non-augmented synthetic control and plot the results (both pre-treatment fit and post-treatment differences). Also report the average ATT and L2 imbalance.

```
# non-augmented synthetic control
syn <-                                  # save object
  augsynth(uninsured_rate ~ treatment, # treatment - use instead of treated bc latter codes 2012.25 as
                          State,     # unit
                          year,  # time
                          medicaid_expansion,    # data
           progfunc = "None",        # plain syn control
           scm = T)                  # synthetic control
```

```
## One outcome and one treatment time found. Running single_augsynth.
```

```r
# Plot results
plot(syn)
```




```r
#Also report the average ATT and L2 imbalance
summary_stats <- summary(syn)
summary_stats
```

```
##
## Call:
## single_augsynth(form = form, unit = !!enquo(unit), time = !!enquo(time),
##     t_int = t_int, data = data, progfunc = "None", scm = ..2)
##
## Average ATT Estimate (p Value for Joint Null):  -0.00827   ( 0.06 )
## L2 Imbalance: 0.001
## Percent improvement from uniform weights: 99.1%
##
## Avg Estimated Bias: NA
##
## Inference type: Conformal inference
##
##  Time Estimate 95% CI Lower Bound 95% CI Upper Bound p Value
##  2014   -0.008             -0.026              0.009   0.154
##  2015   -0.005             -0.022              0.012   1.000
##  2016   -0.011             -0.028              0.007   0.860
##  2017   -0.011             -0.028              0.006   0.844
```

```
##  2018   -0.011             -0.028             0.006   1.000
##  2019   -0.005             -0.022             0.012   1.000
##  2020   -0.007             -0.024             0.010   1.000
```

```
# Average ATT Estimate (p Value for Joint Null):  -0.00827   ( 0.068 )
# L2 Imbalance: 0.001
```

- Re-run the same analysis but this time use an augmentation (default choices are Ridge, Matrix Completion, and GSynth). Create the same plot and report the average ATT and L2 imbalance.

```
# augmented synthetic control
# recalculate with Ridge function that penalizes really high weights
# ----------------------------------------------------------------
ridge_syn <-
  augsynth(uninsured_rate ~ treatment,
                          State,     # unit
                          year,  # time
                          medicaid_expansion,
           progfunc = "ridge",  # specify
           scm = T)
```

```
## One outcome and one treatment time found. Running single_augsynth.
```

```
summary(ridge_syn)
```

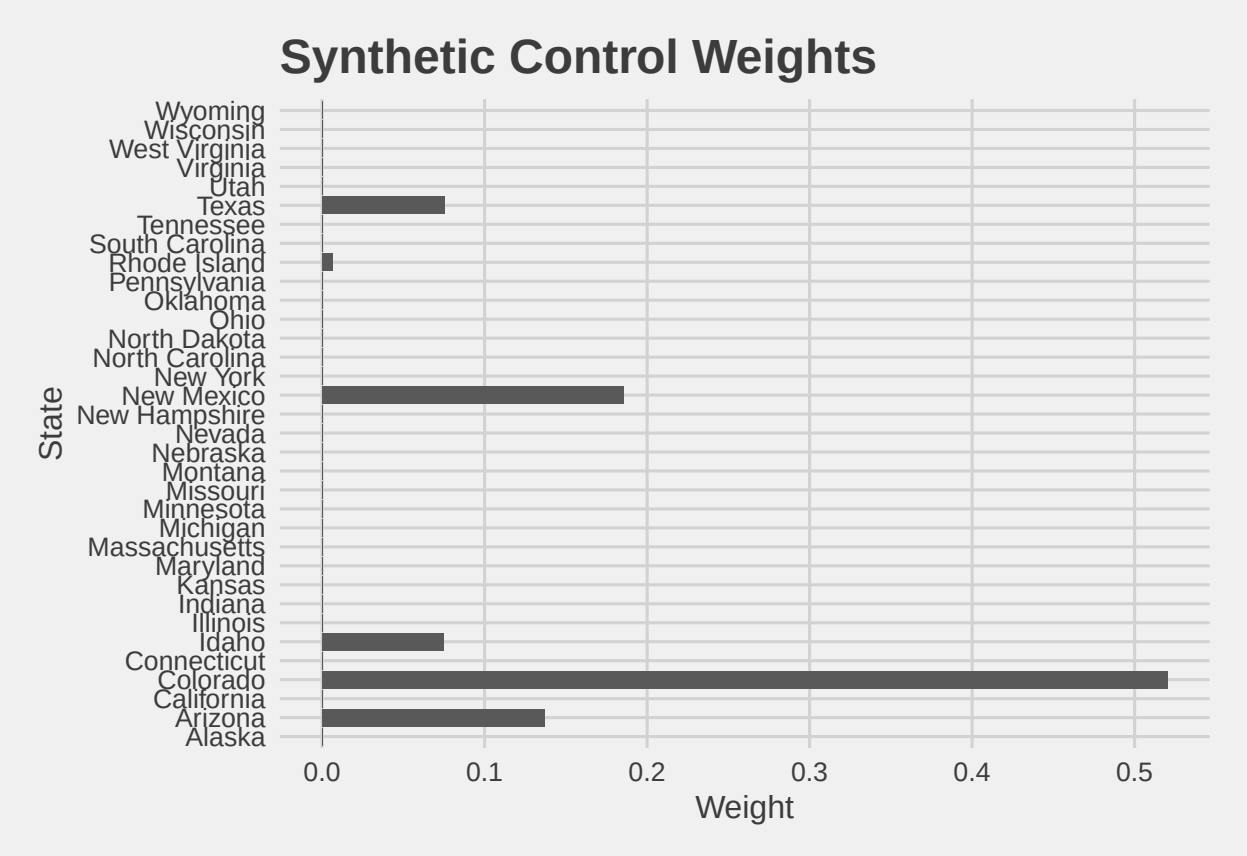
```
##
## Call:
## single_augsynth(form = form, unit = !!enquo(unit), time = !!enquo(time),
##     t_int = t_int, data = data, progfunc = "ridge", scm = ..2)
##
## Average ATT Estimate (p Value for Joint Null):  -0.00828   ( 0.052 )
## L2 Imbalance: 0.001
## Percent improvement from uniform weights: 99.1%
##
## Avg Estimated Bias: 0.000
##
## Inference type: Conformal inference
##
##  Time Estimate 95% CI Lower Bound 95% CI Upper Bound p Value
##  2014   -0.008             -0.026             0.009   0.133
##  2015   -0.005             -0.022             0.012   1.000
##  2016   -0.011             -0.028             0.007   0.846
##  2017   -0.011             -0.028             0.006   0.846
##  2018   -0.011             -0.028             0.006   1.000
##  2019   -0.005             -0.022             0.012   1.000
##  2020   -0.007             -0.024             0.010   1.000
```

```
# Average ATT Estimate (p Value for Joint Null):  -0.00828   ( 0.052 )
# L2 Imbalance: 0.001
```

- Plot barplots to visualize the weights of the donors.

```r
# barplots of weights

data.frame(syn$weights) %>% # coerce to data frame since it's in vector form
  # process
  # ---------
  # change index to a column
  tibble::rownames_to_column('State') %>% # move index from row to column (similar to index in row as i
  filter(syn.weights > 0) %>% # filter out weights less than 0
  # ---------
  ggplot() +
  # stat = identity to take the literal value instead of a count for geom_bar()
  geom_bar(aes(x = State,
               y = syn.weights),
           stat = 'identity') +  # override count() which is default of geom_bar(), could use geom_col(
  coord_flip() +   # flip to make it more readable
  # themes
  theme_fivethirtyeight() +
  theme(axis.title = element_text()) +
  # labels
  ggtitle('Synthetic Control Weights') +
  xlab('State') +
  ylab('Weight')
```



HINT: Is there any preprocessing you need to do before you allow the program to automatically find weights for donor states? I created the treatment variable.

Discussion Questions

- What are the advantages and disadvantages of synthetic control compared to difference-in-differences estimators?
- **Answer**: Synthetic control is more flexible in some ways as it creates a weighted combination of control units to match the treated unit. It can help fix unobserved heterogeneity and it's useful when we have small samples to use synthetic control instead of DiD. However, synthetic control is reliant on model specifications and can be complicated to interpret compared to DiD.
- One of the benefits of synthetic control is that the weights are bounded between [0,1] and the weights must sum to 1. Augmentation might relax this assumption by allowing for negative weights. Does this create an interpretation problem, and how should we balance this consideration against the improvements augmentation offers in terms of imbalance in the pre-treatment period?
- **Answer**: Yes. It can create interpretation problems. Negative weights sound counterintuitive because it means that controls are different from treated units. We'd also want to gut check our research question to make sure that this would make theoretical sense. We could also conduct a sensitivity analysis by checking how much information we get from negative weights.

Staggered Adoption Synthetic Control

Estimate Multisynth

Do the following:

- Estimate a multisynth model that treats each state individually. Choose a fraction of states that you can fit on a plot and examine their treatment effects.

```
# ppool_syn <- multisynth(uninsured_rate ~ treated,
#                         State,                          # unit
#                         year,                           # time
#                         nu = 0.5,                       # varying degree of pooling
#                         multi, # data
#                         n_leads = 10)                   # post-treatment periods to estimate
# with default nu
# ---------
ppool_syn <- multisynth(uninsured_rate ~ treated,
                        State,                          # unit
                        year,                           # time
                        multi,  # data
                        n_leads = 10)                   # post-treatment periods to estimate

# view results
print(ppool_syn$nu)
```

```
## [1] 0.2998142
```

```
ppool_syn
```

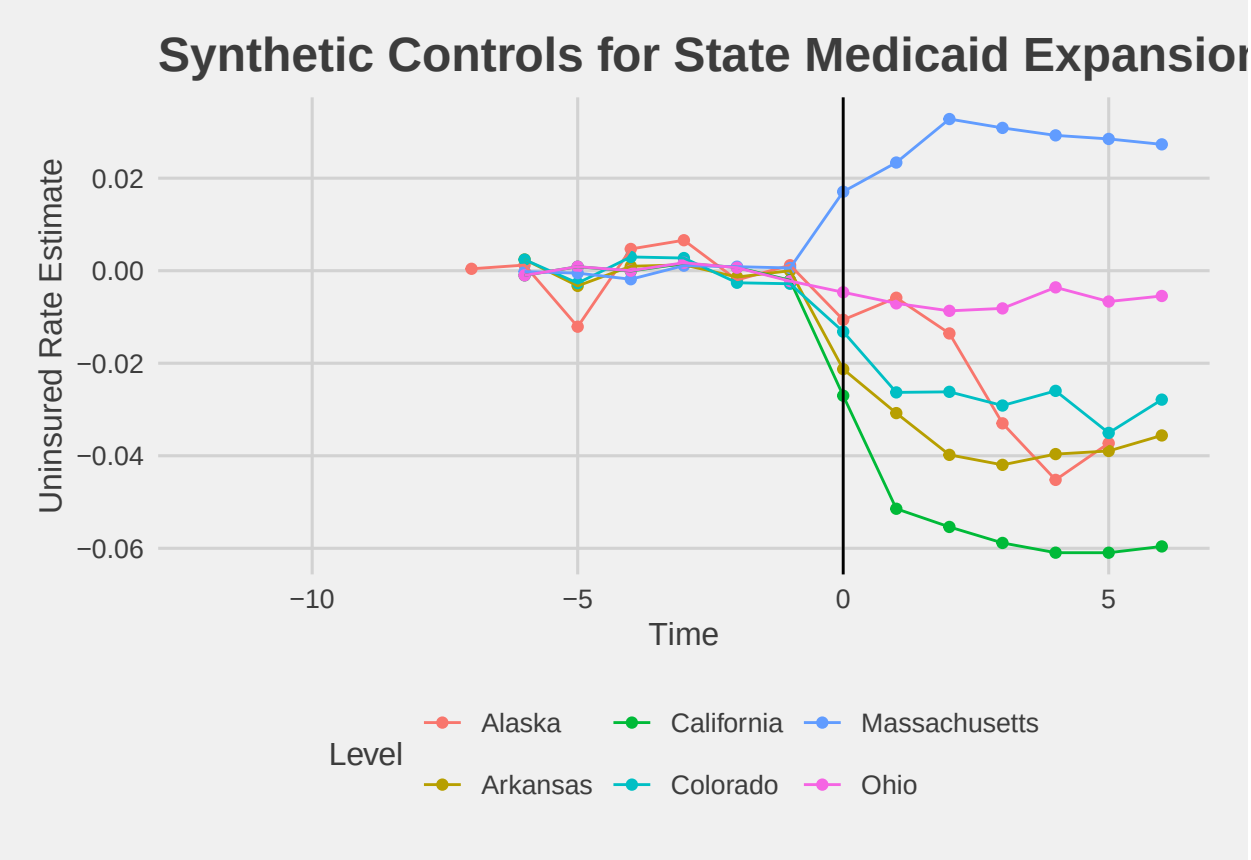
```
##
## Call:
## multisynth(form = uninsured_rate ~ treated, unit = State, time = year,
##     data = multi, n_leads = 10)
##
## Average ATT Estimate: -0.017
```

```
ppool_syn_summ <- summary(ppool_syn)
```

```
# Specify small subset
desired_levels <- c("Alaska", "Arkansas","Alabama", "California", "Colorado", "Ohio", "Massachusetts",
# Filter data for the desired states
filtered_data <- ppool_syn_summ$att %>%
  filter(Level %in% desired_levels)
# Plot
filtered_data %>%
  ggplot(aes(x = Time, y = Estimate, color = Level)) +
  geom_point() +
  geom_line() +
  geom_vline(xintercept = 0) +
  theme_fivethirtyeight() +
  theme(axis.title = element_text(),
        legend.position = "bottom") +
  ggtitle('Synthetic Controls for State Medicaid Expansion') +
  xlab('Time') +
  ylab('Uninsured Rate Estimate')
```

```
## Warning: Removed 42 rows containing missing values or values outside the scale range
## (`geom_point()`).
```

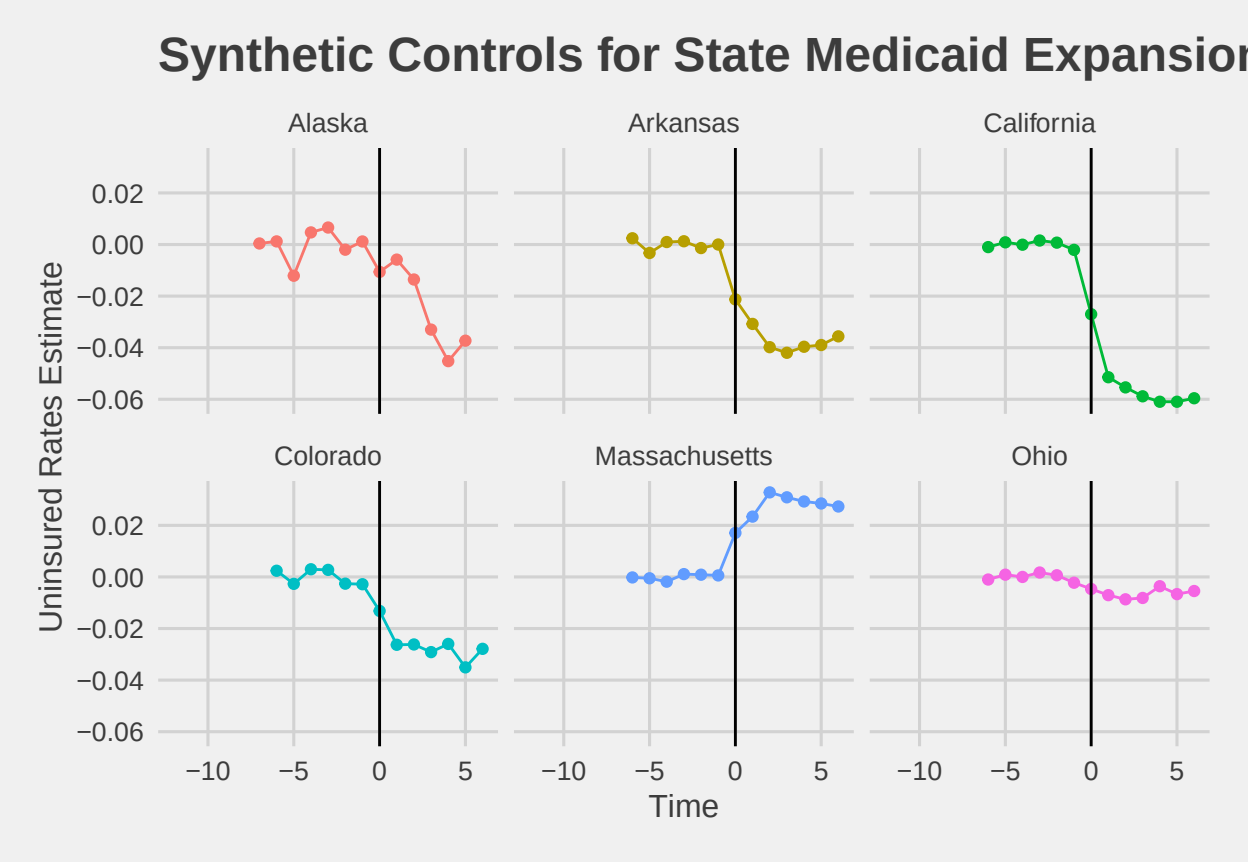
```
## Warning: Removed 42 rows containing missing values or values outside the scale range
## (`geom_line()`).
```




```
# plot actual estimates not values of synthetic controls - use a facet_wrap for readability
# ---------
filtered_data %>%
  ggplot(aes(x = Time, y = Estimate, color = Level)) +
  geom_point() +
  geom_line() +
  geom_vline(xintercept = 0) +
  theme_fivethirtyeight() +
  theme(axis.title = element_text(),
        legend.position = 'None') +
  ggtitle('Synthetic Controls for State Medicaid Expansion') +
  xlab('Time') +
  ylab('Uninsured Rates Estimate') +
  facet_wrap(~Level)    # facet-wrap by level (state in this case) for clearer presentation
```

```
## Warning: Removed 42 rows containing missing values or values outside the scale range
## (`geom_point()`).
```

```
## Warning: Removed 42 rows containing missing values or values outside the scale range
## (`geom_line()`).
```



- Estimate a multisynth model using time cohorts. For the purpose of this exercise, you can simplify the treatment time so that states that adopted Medicaid expansion within the same year (i.e. all states that adopted epxansion in 2016) count for the same cohort. Plot the treatment effects for these time cohorts.

```
# multisynth model time cohorts
ppool_syn_time <- multisynth(uninsured_rate ~ treated,
                             State,
                             year,
                             multi,
                             n_leads = 10,
                             time_cohort = TRUE)           # time cohort set to TRUE

# save summary
ppool_syn_time_summ <- summary(ppool_syn_time)

# view
ppool_syn_time_summ
```

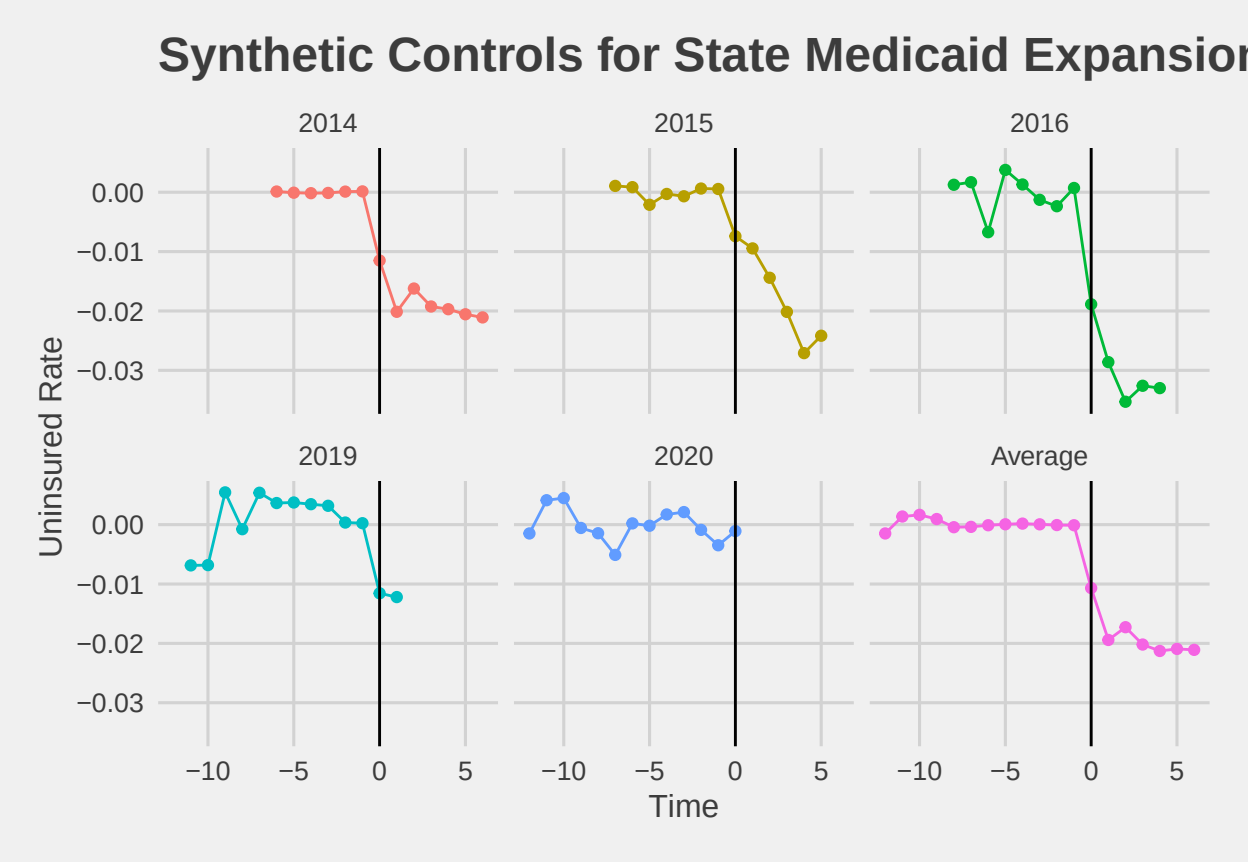
```
##
## Call:
## multisynth(form = uninsured_rate ~ treated, unit = State, time = year,
##     data = multi, n_leads = 10, time_cohort = TRUE)
##
## Average ATT Estimate (Std. Error): -0.017  (0.006)
```

```
##
## Global L2 Imbalance: 0.001
## Scaled Global L2 Imbalance: 0.008
## Percent improvement from uniform global weights: 99.2
##
## Individual L2 Imbalance: 0.005
## Scaled Individual L2 Imbalance: 0.017
## Percent improvement from uniform individual weights: 98.3
##
##  Time Since Treatment   Level    Estimate   Std.Error lower_bound  upper_bound
##                     0 Average -0.01068255 0.004828774 -0.02104673 -0.001961552
##                     1 Average -0.01942100 0.006029684 -0.03142681 -0.008607062
##                     2 Average -0.01727609 0.005878019 -0.02894542 -0.006475934
##                     3 Average -0.02019425 0.006222753 -0.03282509 -0.009002417
##                     4 Average -0.02127762 0.006103968 -0.03374563 -0.010438341
##                     5 Average -0.02093346 0.005767378 -0.03206622 -0.010318718
##                     6 Average -0.02108744 0.006277225 -0.03346102 -0.009229644
```

```
ppool_syn_time_summ$att %>%
  ggplot(aes(x = Time, y = Estimate, color = Level)) +
  geom_point() +
  geom_line() +
  geom_vline(xintercept = 0) +
  theme_fivethirtyeight() +
  theme(axis.title = element_text(),
        legend.position = 'None') +
  ggtitle('Synthetic Controls for State Medicaid Expansion') +
  xlab('Time') +
  ylab('Uninsured Rate') +
  facet_wrap(~Level)
```

```
## Warning: Removed 36 rows containing missing values or values outside the scale range
## (`geom_point()`).
```

```
## Warning: Removed 36 rows containing missing values or values outside the scale range
## (`geom_line()`).
```



Discussion Questions

- One feature of Medicaid is that it is jointly administered by the federal government and the states, and states have some flexibility in how they implement Medicaid. For example, during the Trump administration, several states applied for waivers where they could add work requirements to the eligibility standards (i.e. an individual needed to work for 80 hours/month to qualify for Medicaid). Given these differences, do you see evidence for the idea that different states had different treatment effect sizes?
- **Answer**: Yes– some states have have stricter work requirements, such as Ohio, and see very little difference in uninsured rates. California has a different treatment effect size.
- Do you see evidence for the idea that early adopters of Medicaid expansion enjoyed a larger decrease in the uninsured population?
- **Answer**: The multisynth model suggests that 2015 and 2016 adopters had a larger decrease in uninsured population compared to 2019 and 2014 (late and early). I also expect some disruption due to Medicaid continuous enrollment policies during COVID and subsequent PHE unwinding so it's possible that 2015 and 2016 will be the "best" years to adopt. # General Discussion Questions
- Why are DiD and synthetic control estimates well suited to studies of aggregated units like cities, states, countries, etc?
- **Answer**: DiD is good for studying aggregated units because we can control for time-varying confounders. We can use pre-existing time trends to help establish a causal relationship. With parallel trends assumptions we don't need to control for a whole bunch of covariates. And similar to RD, it's a intuitive design and easy to explain.

- What role does selection into treatment play in DiD/synthetic control versus regression discontinuity? When would we want to use either method?
- **Answer**: RD requires a cutoff /threshold variable and a lot of datapoints right above and below the cutoff. To me the two big differences are that RD typically takes out the role of selection in treatment by taking advantage of this cut off. Whereas diff in diff and synthetic control uses the parallel assumption but selection can be a big issue. I'd use RD when I have individual level data and a clear cut off, and DiD when I have more time to observe trends and for units like states or countries.